Army Research Laboratory

Impact of Cognitive Architectures on Human-Computer Interaction

by Sidney C Smith

ARL-TR-7092 **September 2014**

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ARL-TR-7092 **September 2014**

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REPORT DOCUMENTATION PAGE			*Form Approved* *OMB No. 0704-0188*
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1. REPORT DATE *(DD-MM-YYYY)* September 2014	**2. REPORT TYPE** Final		**3. DATES COVERED (From - To)** January 2014–June 2014
4. TITLE AND SUBTITLE Impact of Cognitive Architectures on Human-Computer Interaction			**5a. CONTRACT NUMBER**
			5b. GRANT NUMBER
			5c. PROGRAM ELEMENT NUMBER
6. AUTHOR(S) Sidney C Smith			**5d. PROJECT NUMBER**
			5e. TASK NUMBER
			5f. WORK UNIT NUMBER
7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES) US Army Research Laboratory ATTN: RDRL-CIN-S Aberdeen Proving Ground, MD 21005-5069			**8. PERFORMING ORGANIZATION REPORT NUMBER** ARL-TR-7092
9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)			**10. SPONSOR/MONITOR'S ACRONYM(S)**
			11. SPONSOR/MONITOR'S REPORT NUMBER(S)
12. DISTRIBUTION/AVAILABILITY STATEMENT Approved for public release; distribution is unlimited.			
13. SUPPLEMENTARY NOTES Author email: <sidney.c.smith24.civ@mail.mil>			
14. ABSTRACT Researchers have been developing, using, and implementing cognitive architectures in an attempt to understand how humans gather, process, and use information. Cognitive architectures have been used to advance the study and application of artificial intelligence. They have also been used to predict human performance and, in so doing, evaluate user interfaces. In this report we will review the influence of several cognitive architectures—specifically, asking what promises were made, what impacts were realized, and what potential impact can we reasonably expect in the future.			
15. SUBJECT TERMS human-computer interaction (HCI), cognitive architectures, ACT-R, CLARION, EPIC, Soar			

16. SECURITY CLASSIFICATION OF:			**17. LIMITATION OF ABSTRACT**	**18. NUMBER OF PAGES**	**19a. NAME OF RESPONSIBLE PERSON** Sidney C Smith
a. REPORT Unclassified	**b. ABSTRACT** Unclassified	**c. THIS PAGE** Unclassified	UU	18	**19b. TELEPHONE NUMBER** (*Include area code*) 410-278-6235

Standard Form 298 (Rev. 8/98)
Prescribed by ANSI Std. Z39.18

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1. Introduction

Newell and Card observed a phenomenon that they related to Gresham's law, which states, "Bad money drives out good."[1] Sir Thomas Gresham noticed that the newer coins were considered more valuable; therefore, they began to disappear from circulation because people would rather pay with the older coins, which were considered less valuable. Mundell argues that the expression is backwards and should be rendered, "Good money drives out bad."[2] I suppose it depends upon whether the buyers or the sellers have more control over the currency. Newell applies this same logic to science and observes that "hard science drives out soft."[1] Using three examples—Operations Research, Human Factors, and Programming Languages—Newell and Card illustrate how the hard sciences of linear programming, engineering, and parsing have relegated the soft sciences into the background. I have seen this in software engineering, where the hard functional requirements push the soft nonfunctional requirements into the background. Our terminology, functional versus nonfunctional, displays the bias. We all agree that usability, maintainability, and security are important, but since we do not really know how to measure these things, they take a back seat to things that we can measure.

Working as an information assurance professional for 10 years, I have found that the progression of security is directly proportional to our ability to measure it. Newell and Card are convinced that for psychology to remain relevant in human-computer interaction (HCI), it must harden. Their vision is for psychology to provide engineering style theory that influences the design of computer interfaces. They acknowledge that there are competing visions. One vision uses psychology primarily as an evaluation tool. The other vision provides an explanation where the work is done to prove that the theory is correct and not to provide useful tools to designers. While acknowledging the value of these visions, Newell and Card clearly state, "They will never beat Gresham's Law."[1] Hardening a science is difficult, and Newell and Card acknowledge four major obstacles to realizing their vision: psychology, as it applies to computer interfaces, is too low level, the scope is too limited, it is too late, and it is too difficult to apply.[1] The hardest science in this space deals with cognitive architectures and makes use of Fitts's Law,[3] which provides empirical data that may be used to provide numbers that designers may incorporate into their designs. Card et al. used this kind of science when they built the Model Human Processor and the Goals, Operations, Methods, and Selection (GOMS) model, which they used to investigate text editing with a line editor on a teletype machine.[4] One of the key issues is that the problems designers are trying to solve are much bigger than the problems researchers are investigating.

Moreover, the findings in the research do not scale up to solving the problems of the designers. Newell and Card demonstrate that the average life cycle of a user interface device is about 20 years. By 1985 when they had completed their work, teletype machines had been replaced by glass terminals, and line editors had been replaced by full screen visual editors. By the time I started my career in 1989, teletypes where a relic of the past, and the only ones I ever saw were the consoles of Digital Equipment Corporation Virtual Address eXtension DEC VAX 11-785 super minicomputers that were themselves considered old at the time. Because of the rapid changes in techonology, by the time the research is concluded and the findings have been published, the results are difficult to apply to modern technologies.

In this report, I will examine the progress that has been made since 1985 to discover how successfully the science has been hardened and gauge the realization of Newell and Card's vision. In Section 2, I will review some of the cognitive architectures being used in HCI. In Section 3, I will outline some of the early promises made in this field. In Section 4, I will cover the applications of cognitive architectures. In Section 5, I will conclude by comparing the promises of Section 3 to the deliveries in Section 4.

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2. Cognitive Architectures Overview

Cognitive architectures are used to express the psychological theories in a quantitative format to drive the models necessary to allow application designers to design more usable systems and to generate intelligent behavior.[5] They are also focused on those aspects that are constant over time. Langley et al. related this to a building, saying, "There is also a direct analogy with a building's architecture, which consists of permanent features like its foundation, roof, and rooms, rather than its furniture and appliances, which one can move or replace."[5] The goals of quantitative models and intelligent behavior are complementary, and each serves to mature or harden this science. Langley et al. include brief summaries of 18 separate cognitive architectures, but focus on only 4.[5] In a similar manner we will focus on only a few architectures.

2.1 The Atomic Components of Thought–Rational (ACT-R)

In their book *The Atomic Components of Thought*, Anderson and Lebiere present their ACT-R cognitive model, which they claim "consists of a theory of the nature of human knowledge, a theory of how this knowledge is deployed, and a theory of how that knowledge is acquired."[6] ACT-R is composed of modules that communicate with a central production system through

buffers. The number of modules is not key to the theory, and more may be added as necessary. Theories and techniques have been incorporated from other cognitive architectures like Executive Process–Interactive Control (EPIC) cognitive architecture. The core is the buffering to the central production system because the central production system may work with only the data that currently reside in its buffers. Anderson et al. go to great lengths to show how their architecture maps to the regions of the brain as seen in integrated brain imaging.[7]

2.2 CLARION

The CLARION cognitive architecture is composed of four subsystems: the action-centered-centered subsystem (ACS), the non-action-centered subsystem (NACS), the motivational subsystem (MS), and the meta-cognitive subsystem (MCS).[8] Each of these subsystems has both an implicit and explicit representational structure. The ACS uses neural networks to compute the quality of each action. It then selects the action with the highest quality. There is a Q-learning algorithm that improves this assessment over time. The NACS provides the memory for the architecture. MS sets the goals and evaluates whether the goal has been achieved. The MCS monitors the system to improve its cognitive performance.[8]

2.3 EPIC

David Kieras and David Meyer presented the EPIC cognitive architecture and used it to explore human performance.[9] The EPIC cognitive architecture builds upon the Model Human Processor[4] and is composed of a collection of models of human performance, fashioned together by a simplified theory, and tuned using performance information gathered from the literature. To validate the model, they used EPIC to examine common problems in HCI (e.g., choosing an item from a pull-down menu, typing spoken data, and processing multiple visual information sources). For each of these problems the predictions from EPIC were compared to actual human performance.[9] What differentiates EPIC from ACT-R is that EPIC has, from the beginning, used empirical data to provide constraints on the model, like how long it takes a human to move a hand, or the smallest area upon which an eye may focus.

2.4 Soar

The Soar cognitive architecture uses problem spaces connected to a production system that uses subgoaling via impasse detection, learning, and chunking to create a model of human thought.[10] The cognitive architecture was built iteratively with new modules and functionality being added to almost every new version. In 2004 Nuxoll and Laird added episodic memory to the Soar architecture.[11] In 2008 Laird presented extensions to Soar that included nonsymbolic

representation, new learning mechanisms, and long-term memories. These extensions enable working memory activation, reinforced learning, emotion, semantic memory, episodic memory, and visual imagery.[12] In 2010 Rosenbloom created a variant of the Soar architecture based upon graphical models.[13]

3. Early Promises

Over the years researchers investigating cognitive architectures have identified the potential in these models to impact HCI. Newell and Card discussed sound theories coming out of cognitive architecture that would be used by interface designers the same way that engineers use the theories of physics to build bridges.[1] They also envisioned a design tool that would have the theories and the quantitative data embedded inside of it, providing this capability to the designer while insulating the designer from it.[1] Kieras and Meyer talked about using cognitive architectures to predict human performance and to compare different user interface approaches.[9] Langley et al. discussed using cognitive architectures to simulate humans for pedagogical or entertainment purposes.[5] Pirolli asserted that psychology ought to be able to answer questions about how to design application programs.[14] In their 1990 work, Olson and Olson identified five roles for cognitive architectures:[15]

> 1. Initially constraining the design space, so that one does not build an interface, for example, that requires more items to be kept in memory than will fit in working memory (WM).
>
> 2. Answering specific design decisions, so that one can decide, for example, between a dialogue that requires few keystrokes but difficult retrieval from memory or one that involves more keystrokes but is easier to remember.
>
> 3. Estimating the total time for task performance with sufficient accuracy to make decisions about how many people are needed to staff the performance of a repetitive operational task on a computer.
>
> 4. Providing the base from which both to calculate training time and to guide training documentation to help the user determine in which situations which method is most efficient.
>
> 5. Knowing which stages of activity take the longest time or produce the most errors, in directing research toward the aspects of human-computer interaction that will have strong future performance implications.

With the exception of using cognitive architecture to simulate humans, I believe that their list provides a useful summary of the early promises of cognitive architectures to the HCI community.

4. Applications of Cognitive Architectures

In the last 30 years since Newell and Card published their work on the prospects of this technology, researchers have made significant progress. Space will not permit an exhaustive summary; however, I have highlighted some of this work:

- John and Vera were able to use GOMS analysis and the Soar cognitive architecture to predict the behavior of an expert using a highly interactive machine-based graphic task (i.e., a video game) with a 60% success rate.[16]
- Gray et al. used GOMS analysis in Project Ernestine to compare the time it took telephone company operators to complete certain tasks.[17] This study showed that the performance of a new workstation was actually slower than the previous workstation. Their theoretical findings were validated with empirical data.[17]
- Byrne reported the work of Nelson et al. in constructing the NASA Test Director (NTD) simulator in NTD-Soar.[18] This simulation was able to perform the 3,000 pages of tasks that an NTD would need to perform before a launch. Although this simulation probably will not be used to launch spacecraft, it could be used to test new interfaces to automate some of the NTD's work.[18]
- Chella et al. proposed a cognitive architectural approach to the solve problems with artificial vision for an autonomous agent.[19]
- Huguenard et al. conducted a study of telephone menus and discovered that contrary to prevailing wisdom, smaller menus do not reduce error rate. The cognitive architecture provided a theoretical explanation of why this happened.[20]
- Sweller et al. described their use of cognitive architectures for designing curriculum.[21]
- Byrne used the ACT-R cognitive architecture to successfully predict human performance in menu selection.[22]

- Cockburn et al. used the Hick-Hyman and Fitts's law to compare 4 different menu technologies: traditional, recency, frequency, and adaptive. They compared their results with empirical data and found that they matched extremely well.[23]

- Hornof used the EPIC cognitive architecture to compare the performance of several different visual layouts.[24]

- Salvucci successfully used the ACT-R cognitive model to explain and predict the effects of distraction upon driving an automobile.[25]

- Magerko et al. used the Soar cognitive architecture to implement characters in a computer game based upon Unreal Tournament.[26] They observed that every computer game in existence is proof that you do not need realistic artificial intelligence (AI) in the nonplayer characters (NPCs) for the game to be enjoyable. They lamented that many of the most popular games like *Quake* have very limited violent adversarial relations with the NPCs, which are basically just "computerized punching bags."[26] Their goal is to create a nonviolent, plot driven game that really needs AI characters. The basic framework for this game is complete, and now they are enriching it toward their ultimate goal.[26]

- Tambe et al. are using cognitive architectures to simulate human pilots in a battlefield simulation. In this work they were preparing for the Synthetic Theatre of War-1997 exercise where between 10,000 and 50,000 automated agents would work with up to 1,000 humans.[27] The results of this exercise are documented by Laird et al.[28]

5. Conclusions and Future Work

To assess whether cognitive architectures have been able to fulfill their potential, in the following paragraphs, I will take each role as outlined by Olson and Olson, plus the promises of simulated humans, and compare it against the accomplishments listed in Section 3:

- Role #1: "Initially constraining the design space, so that one does not build an interface, for example, that requires more items to be kept in memory than will fit in working memory (WM)."[15] Miller's rule of 7, plus or minus 2,[29] has made its way into the mainstream of interface design thinking. It is not clear to me that cognitive architectures played a significant role in establishing this rule; however, this is clearly a case where psychology has influenced interface design.

- Role #2: "Answering specific design decisions, so that one can decide, for example, between a dialogue that requires few keystrokes but difficult retrieval from memory or one that involves more keystrokes but is easier to remember."[15] Byrne's work on menu selection,[18] Cockburn et al.'s work on menu technology,[23] and Hornof's work on visual layout[24] show that cognitive architectures are indeed being used to fill the role; however, it seems that these tools still have not made their way into the hands of interface designers. When Tullis et al. were considering navigation architectures for a redesign of the Fidelity Regional Security & Operations Website, no consideration was given to the information gained from cognitive architectures. They simply used intuition and imitation to create 6 navigation strategies and conducted a usability study to discover which worked the best.[30]

- Role #3: "Estimating the total time for task performance with sufficient accuracy to make decisions about how many people are needed to staff the performance of a repetitive operational task on a computer."[15] The work of Gary et al. on Project Ernestine demonstrates the value of cognitive architectures for this purpose.

- Role #4: "Providing the base from which both to calculate training time and to guide training documentation to help the user determine in which situations which method is most efficient."[15] Sweller et al. demonstrate that cognitive architectures can and have been used for this purpose.

- Role #5: "Knowing which stages of activity take the longest time or produce the most errors, in directing research toward the aspects of human-computer interaction that will have strong future performance implications."[15] Huguenard et al.'s work with phone menus demonstrates how cognitive architectures may be used for this purpose.

- Role #6: Providing a simulated human in simulated environments for training and entertainment. The work of Magerko et al. and Tambe et al. demonstrates the ability of cognitive architectures to fulfill this role.

Although there has been work which demonstrates that cognitive architectures are capable of fulfilling each of the roles promised by early researchers, we are still a long way from the vision Newell and Card described where psychology would provide design principles that would be used by interface designers. Interface designers are still more likely to use intuition and imitation to complete their work rather than consult psychologist and cognitive models. This might be the time for the technology to establish itself in Website design. World Wide Web applications are mature enough for the research to be able to provide relevant information. Palmer's study clearly indicates that more usable Websites have the ability to generate more revenue.[31] Increased

revenue may provide the incentive necessary to utilize this technology if it were packaged in a way that was easy for Web designers to use. I can envision a virtual Web user similar to the virtual NTD described earlier that, given a Website and goals, would be able to assess the usability of the site and provide some kind of score and suggestions on improvements. Over the past few months, I have personally used 10 different automated Web usability tools, but almost all of them report on compliance to the legal requirements to support usability of disabled persons. As a later refinement, research into the cultural aspects of Web design may be incorporated.[32,33]

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